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Our research focuses on multi-input multi-output (MIMO) communications over sparse acoustic channels suffering from frequency modulations. An extension of the recently introduced SLIM algorithm, which stands for sparse learning via iterative minimization, is presented to jointly estimate the sparse and frequency modulated acoustic channels. The extended algorithm is referred to as generalization of SLIM (GoSLIM). Moreover, we also consider channel equalization and symbol detection for various MIMO transmission schemes, including both space-time block coding and spatial multiplexing, under the challenging channel conditions. The effectiveness of the proposed approaches is demonstrated using in-water experimental measurements recently acquired during WHOI09 and ACOMM10 experiments. Furthermore, we present a semi-blind equalizer implemented by Gibbs sampling techniques, and verify its power using SPACE08 experimental results.

15. SUBJECT TERMS

Multi-input multi-output underwater acoustic communications, double-selective acoustic channel, generalization of sparse learning via iterative minimization, Alamouti coding, Gibbs sampling

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Robust High Data Rate MIMO Underwater Acoustic Communications

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LONG-TERM GOALS

Achieving reliable communications with high data rates over underwater acoustic communication (UAC) channels has long been recognized as a challenging problem owing to the scarce bandwidth available and the time-varying channels with large delay spread. Fortunately, the underwater environment with multipath scattering makes it possible for multi-input multi-output (MIMO) spatial multiplexing schemes to achieve high data rate UAC. The major challenges of the high data rate MIMO UAC scheme include time-varying channels, long delay spreads, and mutual interferences among the data streams transmitted by the different transducers. These challenges require short and effective training sequences, efficient channel estimation and tracking algorithms, and innovative equalization and decoding strategies. Our long-term goals are to efficiently and effectively tackle these challenges.

OBJECTIVES

The objectives of our proposed research are: 1) to synthesize effective and efficient training sequences with cyclic prefixes for the accurate estimation and prediction of UAC channels, 2) to devise robust and computationally efficient sparse channel estimation and tracking algorithms that can be used to provide statistical properties of the estimated UAC channels, 3) to provide channel updating, equalization, and decoding schemes with good initial conditions to allow improved turbo processing, and 4) to continue the ongoing in-water experimentation and algorithm evaluation activities by continuing our collaborations with WHOI and others.

APPROACH

Training sequence design: We have recently introduced a new cyclic algorithm (called CAN = CA-New) for the local minimization of the ISL metric for efficient aperiodic sequence designs. CAN is based on fast Fourier transform (FFT) operations and can be used virtually for any practically relevant values of the sequence length, which can be up to a million or even larger. We have also extended CAN to generate perfect periodic sequences, which are the so-called constant amplitude zero auto-correlation (CAZAC) sequences. This CAZAC sequence design problem goes back to Norbert Wiener or even Gauss [66]! The mathematicians have shown that for some sequence lengths, there are an infinite number of perfect periodic sequences. We have solved a long-standing perfect periodic

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sequence design problem – finding such sequences (including long sequences) efficiently and effectively. We solved it via exploiting FFTs.

The extended CAN algorithm is referred to as periodic CAN (PeCAN). Unlike most existing sequence construction methods which are algebraic and deterministic in nature, we start the iteration of PeCAN from random phase initializations and then proceed to cyclically minimize the desired metric. In this way, through different random phase initializations, we can find as many different waveforms as we may ever want [65]! The so-generated sequences are difficult to guess by the foe and hence are especially useful as training sequences or as spreading sequences for UAC applications. We will use PeCAN sequences for more in-water experimentations to demonstrate their effectiveness.

Channel Estimation: Through simultaneous transmissions using multiple transmitters, MIMO systems offer enhanced reliability and/or increased data rates compared to their single-input multi-output (SIMO) counterpart. However, in MIMO systems, the multiple transmissions lead to mutual interferences at the receiver. To successfully recover the transmitted data sequences, accurate channel estimation techniques play crucial roles. We focus on MIMO communications over sparse acoustic channels suffering from frequency modulations, which could be caused by motion-induced Doppler shifts. We present an extension of our recently introduced SLIM algorithm, which stands for Sparse Learning via Iterative Minimization, to estimate the sparse and frequency modulated acoustic channels. The extended algorithm is referred to as generalization of SLIM (GoSLIM).

Turbo Processing: We also consider a semi-blind equalizer implemented by Gibbs sampling techniques. The proposed equalizer performs channel estimation and symbol detection in a joint manner for improved performance. Our Turbo processing approach is robust against the inaccuracy of channel estimates.

WORK COMPLETED

By extending the SLIM algorithm to deal with Doppler frequency modulation, we have devised the GoSLIM algorithm to estimate the underlying CIRs and Doppler frequency in a joint manner.

Before proceeding to discuss the channel estimation problem for frequency modulated frequency-selective acoustic channels, it is instructive to review a simpler case, i.e., the channel estimation problem in stationary channels using the SLIM algorithm. For stationary frequency-selective channels, the channel estimation problem at each receiver has the generic form given by $\mathbf{y}=\mathbf{X}\mathbf{h}+\mathbf{e}$, where \mathbf{y} represents the received measurement vector, \mathbf{X} is constructed using the training sequences in the training-directed mode or the previously detected symbols in the decision-directed mode, \mathbf{h} denotes the channel impulse response (CIR) and \mathbf{e} is the additive noise. The channel estimation problem reduces to estimating \mathbf{h} given \mathbf{y} and \mathbf{X} . We consider SLIM for estimating \mathbf{h} and assume that \mathbf{e} is a circularly symmetric independent and identically distributed complex-valued Gaussian random process with zero mean and variance η . Denote diagonal matrix \mathbf{P} as the covariance matrix of the channel taps and its r^{th} diagonal element as P_r and define \mathbf{x}_r as the r^{th} column of \mathbf{X} . SLIM is user parameter free, making it easy to use in practice. Moreover, SLIM exploits the channel sparsity. It is derived based on the maximum a posteriori (MAP) criterion. The SLIM algorithm can be implemented as:

- Step 0: Initialize $h_r = \frac{\mathbf{x}_r^H \mathbf{y}}{\mathbf{x}_r^H \mathbf{x}_r}$.

- Step 1: With the most recent \mathbf{h} , calculate $p_r = |h_r|^2$.
- Step 2: With the most recent \mathbf{P} and η , calculate $\mathbf{h} = (\mathbf{X}^H \mathbf{X} + \eta \mathbf{P}^{-1})^{-1} \mathbf{X}^H \mathbf{y}$.
- Step 3: With the most recent \mathbf{h} , update, $\eta = \frac{\|\mathbf{y} - \mathbf{X}\mathbf{h}\|^2}{d_y}$, where d_y denotes the length of \mathbf{y} .
- Iterate Steps 1-3 until convergence.

For frequency-selective channels that are modulated by a common Doppler frequency, the channel estimation problem at each receiver now becomes $\mathbf{y} = \mathbf{\Lambda} \mathbf{X} \mathbf{h} + \mathbf{e}$. The vectors \mathbf{y} , \mathbf{h} and \mathbf{e} have been defined previously and $\mathbf{\Lambda} = \text{diag}(1, e^{-2j\pi f T_s}, \dots, e^{-2j\pi f T_s (d_y - 1)})$ represents the Doppler shift matrix. In $\mathbf{\Lambda}$, f is the Doppler frequency, our estimate target, and T_s represents the symbol period. Given \mathbf{y} and \mathbf{X} , we consider the extension of the SLIM algorithm, referred to as generalization of SLIM (GoSLIM) to jointly estimate the CIR \mathbf{h} and the underlying Doppler frequency f . The GoSLIM algorithm can be implemented as:

- Step 0: Initialize $h_r = \frac{\mathbf{x}_r^H \mathbf{y}}{\mathbf{x}_r^H \mathbf{x}_r}$ and $f = 0$.
- Step 1: With the most recent \mathbf{h} , calculate $p_r = |h_r|^2$.
- Step 2: With the most recent $\mathbf{\Lambda}$, \mathbf{P} and η , calculate $\mathbf{h} = (\mathbf{X}^H \mathbf{X} + \eta \mathbf{P}^{-1})^{-1} (\mathbf{\Lambda} \mathbf{X})^H \mathbf{y}$.
- Step 3: With the most recent \mathbf{h} , we first calculate $\tilde{\mathbf{x}} = \mathbf{X}\mathbf{h}$. We denote $\tilde{x}(r)$ and $y(r)$ as the r^{th} element of $\tilde{\mathbf{x}}$ and \mathbf{y} , respectively, and obtain $z(r) = y^*(r) \tilde{x}(r)$. Then the Doppler frequency can be calculated as $f = \arg \max_f \text{Re} \left(\sum_{i=1}^{d_y} z(i) e^{-2j\pi f T_s (i-1)} \right)$.
- Step 4: With the most recent $\mathbf{\Lambda}$ and \mathbf{h} , calculate $\eta = \frac{\|\mathbf{y} - \mathbf{\Lambda} \mathbf{X} \mathbf{h}\|^2}{d_y}$.
- Iterate Steps 1-4 until convergence.

For Doppler modulated frequency-selective channels, once the estimate of the Doppler frequency f is available, the receiver can compensate out the adverse effects induced by the Doppler shift and effectively convert the original frequency-modulated channels to stationary frequency-selective channels. This way, various reception schemes that are effective for stationary frequency-selective channels can be equally applied. In particular, we consider both spatial multiplexing schemes including the minimum mean-squared error based RELAX-BLAST algorithm and space-time coding schemes including Alamouti diversity techniques.

We have also proposed a Gibbs sampler based semi-blind equalizer, which performs channel estimation and symbol detection jointly. The equalizer is robust against the inaccuracy of the channel estimation. We have used in-water experimentation data to validate the effectiveness of our approaches.

RESULTS

1. Buzzards Bay Experimental Results

The Buzzards Bay in-water experiment was conducted in December 2009. The 4 transmit transducers with source spacing up to 1 m were suspended from a vessel heaving in a 15 m mid-depth water column. Two separate 4-hydrophone arrays were deployed approximately 1 km and 2 km away from the source array and they will be referred to, respectively, as RB1 and RB2 receiving arrays. Both RB1 and RB2 receiving arrays had 0.21 m spacing between adjacent hydrophones, and they were mounted on an anchored buoy in a mid-water column during the course of data collection. The Doppler shift was mainly caused by the relative motion between the transmitters and receivers. The carrier frequency, the sampling frequency and the symbol rate employed in Buzzards Bay experiment were 30 KHz, 200 KHz and 8 KHz, respectively.

GoSLIM is employed to estimate the underlying CIRs and Doppler frequencies by making use of the shifted PeCAN training sequences periodically allocated in the transmitted sequence. Figure 1 shows the CIR evolution between the active transmitter and the 2nd hydrophone for all the 6 epochs (the reason why we consider the 2nd hydrophone will be explained shortly). One observes that the position of the principal arrival shown in Figure 1 slowly shifts with time due to the fact that both the transmitter array and the receiving hydrophone arrays were mounted on anchored buoys during the course of data collection. Figure 2, on the other hand, plots the evolution of the Doppler frequency for each hydrophone. The reverberating Doppler frequency estimates obtained from the GoSLIM algorithm shows the presence of Doppler shifts.

Space-time coding schemes: Alamouti coding

To investigate the performance of 2Tx-1Rx Alamouti code, the structure of the transmitted sequences is shown in Figure 3. Two synchronized transmitters were used. Each transmitter sent 4 data packets and each data packet was divided into 16 blocks followed by a gap to ensure the absence of inter-packet interferences. In our design, each payload segment, (e.g., **a** or **b** in Figure 3), contains 250 coded QPSK symbols. Taking the segment **a** for example, it is generated, as shown in Figure 3, by feeding 250 source bits into a 1/2 rate convolutional encoder followed by a random interleaver and QPSK modulation. Segment **b**, as well as the segments in other blocks, is similarly generated but with different realizations of the source bits and random interleaver. The resulting uncoded and coded data rates are 7 Kbps and 3.5 Kbps, respectively.

Since each payload block contains a training sequence as shown in Figure3, the reception scheme for each block is performed as follows: the receiver first conducts training-directed channel estimation by making use of the training sequence, and then detects the payload symbols contained in the two payload segments before and after the training sequence. As a consequence, decision-directed estimation is not needed. For the sequence in Figure 3, each block carries 500 QPSK payload symbols. Therefore each epoch carries 32 K symbols (or equivalently, 64 K uncoded bits or 32 K coded bits) and we have 3 epochs for each receiving array. The channel tap number is fixed at 30 for all epochs. The BER results at different receive hydrophones, by averaging over 192 K uncoded bits and 96 K coded bits, are summarized in Table I for each receiving array. One observes from Table I that the 2nd hydrophone of RB1 array yields remarkably high BERs. This can be explained by the fact that the

power of the channel estimate at this hydrophone is persistently lower than that at other hydrophones by almost an order of magnitude, which is evidenced in Figure 1.

Spatial multiplexing schemes: BLAST data

We also designed 4-input BLAST data, which attained a coded data rate of 30 Kbps by leveraging the MIMO scheme. The payload sequence was divided into blocks, each of length 250, and each block was encoded using a $\frac{1}{2}$ convolutional encoder with constraint length 5. The source information is a grayscale Gator mascot shown in Figure 4(a). We made full use of the available resources by transmitting 4 sequences simultaneously and incorporating the measurements acquired from all the 4 hydrophones, establishing a 4×4 MIMO system. Coded BERs of 3.7×10^{-3} , 1.6×10^{-3} and 5.3125×10^{-4} over the entire 32 K source bits are achieved by analyzing epochs "195600", "195730" and "195860", respectively. The corresponding recovered mascot figures are shown in Figures 4(b)-4(d). Note that the mascots are recovered rather accurately.

2. SPACE08 Experimental Results

The SPACE08 in-water experimentation was conducted by WHOI at the Air-Sea Interaction Tower, 2 miles south to the coast of Martha's Vineyard, MA at a water depth of about 15 m. The carrier frequency, available bandwidth and data rate used in the experiments were 13 KHz, 10 KHz and 8 KHz, respectively. We consider a single-input single-output case where the transmitter consecutively sent the same m-sequence (of length 4095) 89 times to a receiving hydrophone 60 m away. The transmitted sequence is not coded, and the modulation scheme is BPSK due to the binary m-sequence.

We compare the performance of Gibbs sampler based semi-blind equalizer with that of two-step equalizers implemented by SLIM+LMMSE and iterative SLIM+LMMSE. To investigate the tracking behavior of the three types of equalizers considered, the block-wise BER performance versus the block index (we have in total 1820 blocks and each block consists of 200 BPSK symbols) is shown in Figure 5 for epoch "2950157". From Figure 5(a), we can see that the SLIM+LMMSE method loses track of the channel around the 1500th block. The iterative SLIM+LMMSE scheme, by iterating between SLIM channel estimation and LMMSE based symbol detection, successfully tracks the entire payload sequence. The Gibbs sampler gives the best detection performance among the three equalizers. Most notably, only 20 out of the total 364200 symbols (bits) are wrongly detected when using the Gibbs sampler.

IMPACT/APPLICATIONS

The natural bandwidth limitations of coherent underwater acoustic channel suggest a technical breakthrough. MIMO signal processing is a promising bandwidth efficient method to high data rate and high quality services. Our promising results are expected to favorably impact high-rate long-range MIMO-UAC designs.

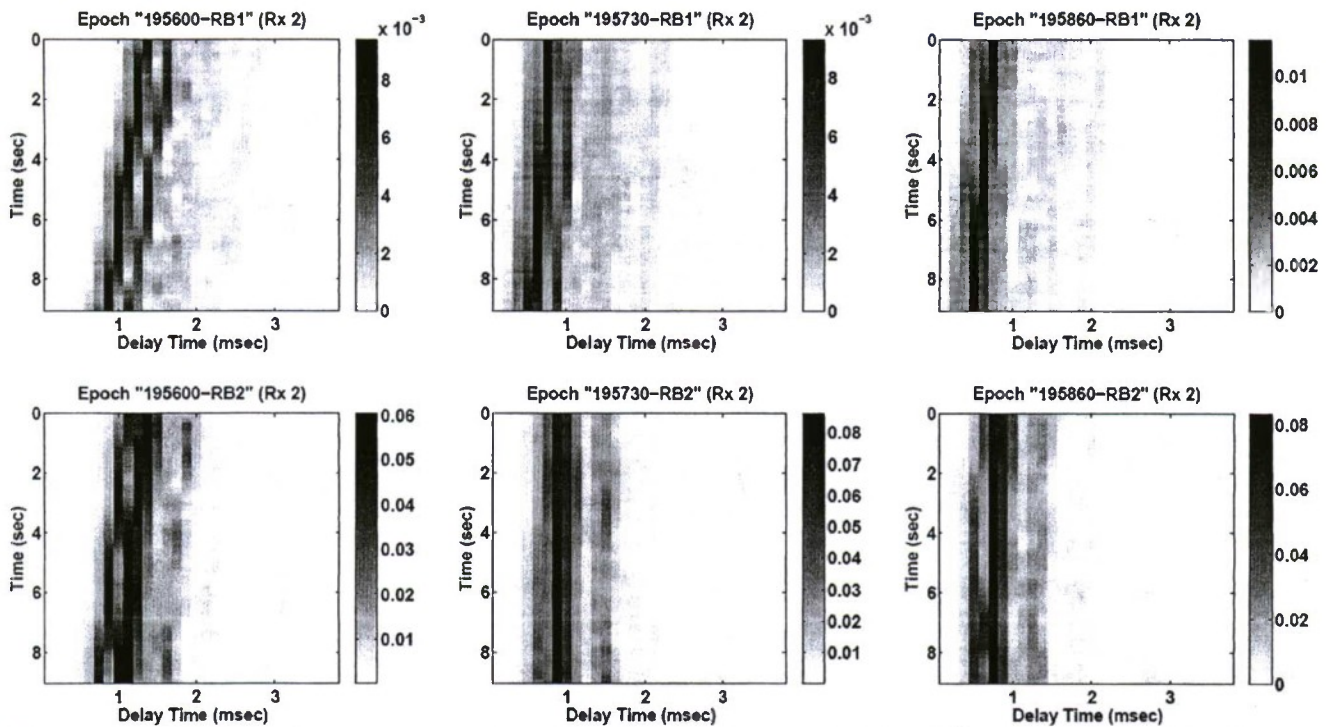


Figure 1: CIR evolution over approximately a 9 second period at the 2nd receiver for all the 6 epochs. [graph: One observes from the GoSLIM CIR estimates that the position of the principal arrival shifts with time. This observation is in line with the fact that both the transmitter array and the receiving hydrophone arrays were mounted on anchored buoys in a mid-water column during the course of data collection in Buzzards Bay in-water experiment.]

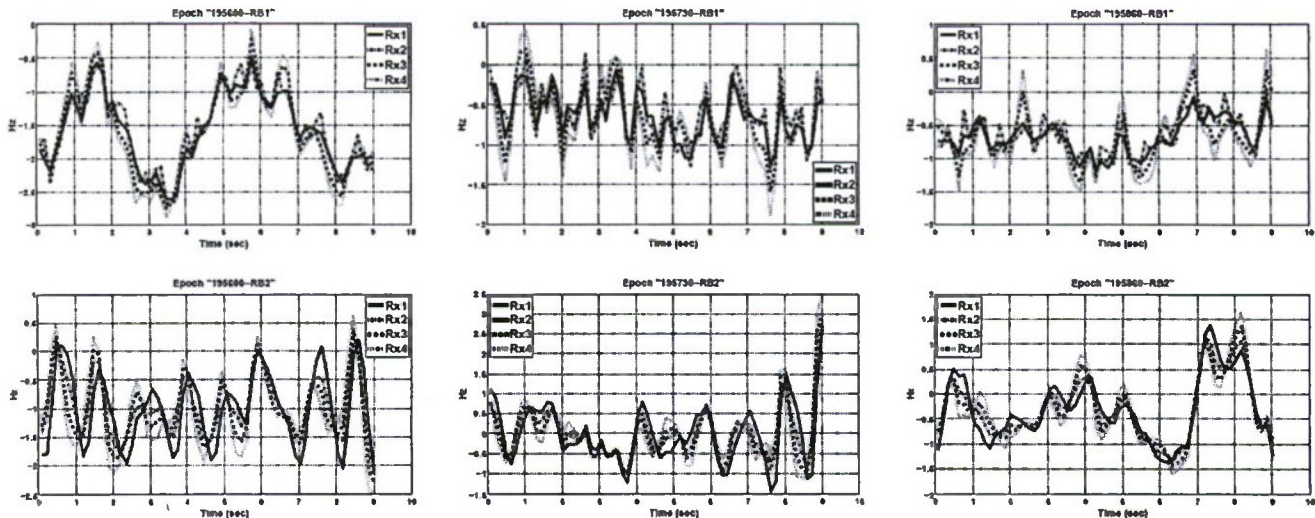


Figure 2: Evolution of the estimated Doppler frequencies at each receiver for all the 6 epochs. [graph: The reverberating Doppler frequency estimates obtained from the GoSLIM algorithm provide evidence on the presence of Doppler shifts.]

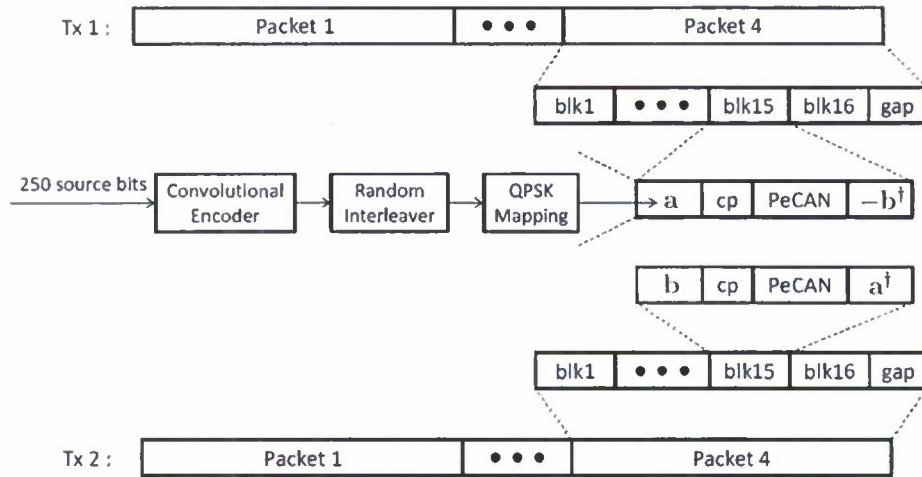


Figure 3: The structure of the transmitted sequence using 2Tx-1Rx Alamouti scheme.
[graph: Each transmitter sends 4 data packets and each packet is divided into 16 blocks. The payload symbols contained in each block are constructed using Alamouti diversity scheme.]

	RB1		RB2	
	uncoded BER	coded BER	uncoded BER	coded BER
Rx1	2.7083×10^{-4}	0	1.8750×10^{-4}	0
Rx2	0.0180	0.0021	1.2500×10^{-4}	0
Rx3	1.6146×10^{-4}	0	6.2498×10^{-5}	0
Rx4	3.2291×10^{-4}	0	1.1458×10^{-4}	0

Table 1: Coded and uncoded BER performance of GoSLIM coupled with Alamouti diversity scheme for 2Tx-1Rx system.

[graph: GoSLIM coupled with Alamouti diversity scheme yields satisfactory detection performance except for the 2nd hydrophone of RB1 receiving array. The reason is that the estimated channel power of this hydrophone is persistently lower than those of other hydrophones by almost an order of magnitude, see Figure 1.]

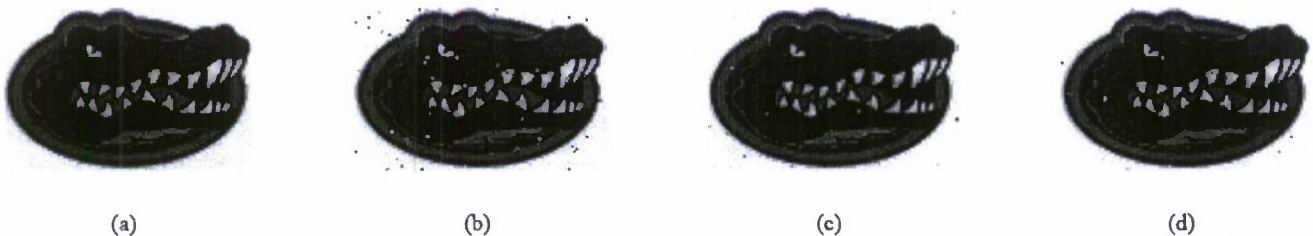


Figure 4: (a) The grayscale Gator mascot transmitted (truth). (b) Mascot recovered from Epoch "195600-RB2". (c) Mascot recovered from Epoch "195730-RB2". (d) Mascot recovered from Epoch "195860-RB2".

[graph: The GoSLIM coupled with RELAX-BLAST scheme effectively recovers the Gator mascot in Buzzards Bay in-water experiment.]

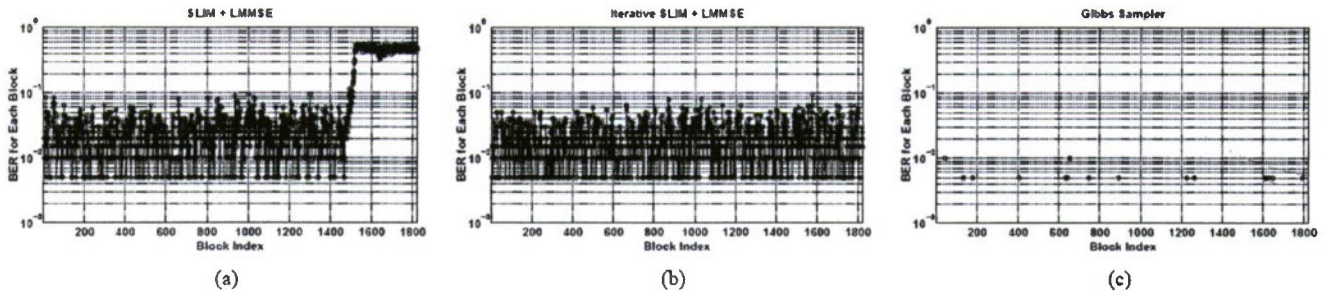


Figure 5: Block-wise BER results for epoch "2950157". (a) SLIM+LMMSE scheme. (b) Iterative SLIM+LMMSE scheme after 2 iterations. (c) Gibbs Sampler based equalizer.
[graph: Statistical equalizer implemented by Gibbs Sampler, which jointly performs CIR estimation and symbol detection, significantly outperforms the conventional two-step equalizer for this severely time-varying channel condition.]

PUBLICATIONS

1. J. Ling, X. Tan, J. Li, and M. L. Nordenvaad, "Efficient channel equalization for MIMO underwater acoustic communications," *Proceedings of 6th Sensor Array and Multichannel Signal Processing Workshop*, Israel, 2010. [in press]
2. J. Ling, H. He, J. Li, P. Stoica, and W. Roberts, "Covert underwater acoustic communications: Transceiver structures, waveform designs and associated performances," *Proceedings of MTS/IEEE Oceans Conference*, Seattle, WA, 2010. [in press]
3. J. Ling, H. He, J. Li, W. Roberts, and P. Stoica, "Covert underwater acoustic communications," *The Journal of the Acoustical Society of America*. [in press]